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8.	**Title of the Research Project**	:	**WATER CONSERVATION STRATEGIES UNDER CLIMATE CHANGE SCENARIOS USING INTEGRATED REMOTE SENSING AND AQUACROP MODELLING FOR WHEAT (*Triticum Aestivum* L.)**

9. Introduction

Accurate estimation of crop production is essential for supporting food availability and guiding long-term agricultural sustainability (Tain *et al*., 2021). Wheat is a key staple crop cultivated across the world and serves as a major source of nutrition for a large portion of the population, making it vital for meeting global food demand (Chen *et al.*, 2023). Recent developments in satellite-based Earth observation have greatly expanded the use of remote sensing approaches for estimating winter wheat yield over large areas.

The crop yield is determined by multiplying the interacting elements, including the soil properties, prevailing climatic conditions, weather fluctuations, and management practices adopted in the field (Xu *et al*., 2019). To estimate yield, researchers commonly rely on both process-based and statistical modelling approaches. Process-based models, particularly crop growth models, simulate the progression of crop development and yield formation over time. However, their use over larger spatial extents is often constrained due to the need for detailed

information on crop characteristics, soil attributes, and prevailing weather conditions (Coa *et al*., 2020; Li *et al.,* 2022).

In contrast, statistical methods derive yield estimates by linking output levels with important crop-related and environmental factors. In this context, remote sensing serves as a valuable tool by offering reliable and spatially extensive datasets needed for such analyses (Cai *et al*., 2022). Its ability to capture information across wide areas and multiple spectral bands makes it particularly useful for evaluating crop conditions, including growth status, pest and disease occurrence, and weed presence (Mishra *et al*., 2022). Among different indicators derived from satellite data, vegetation indices are commonly used to estimate crop yield. These indices provide a clearer representation of changes in vegetation condition than direct reflectance measurements. They are especially sensitive to changes in crop growth and physiological status, which makes them suitable for monitoring crop performance and improving the reliability of yield estimation (Khan *et al*., 2022).

The crop yield estimation is the key component in agricultural management and planning. Traditional approaches, such as agro-meteorological models and field-based sampling, have been widely used; however, these methods are often time-consuming and costly. In contrast, combining satellite-derived information with crop simulation models offers a more effective and dependable method for estimating agricultural yields at regional levels (Ma *et al.,* 2013). Remote sensing techniques enable the assessment of crop growth environment over the large areas and help in understanding the influence of environmental factors on crop development. One effective approach for integrating remote sensing with crop models is the adjustment or reparameterization of model inputs to improve the agreement between the simulated and observed results (Zhao *et al*., 2013). In addition, satellite-based remote sensing products with the high spatial and temporal resolution offer a cost-effective means of collecting data for crop production estimation (Tadesse *et al*., 2015). Several studies have also utilized remote sensing-derived indicators as proxies for yield estimation (e.g., Tadesse *et al*., 2015; Kassie *et al*., 2013; Mann and Warner, 2017). Such information is especially valuable for examining how vegetation indices are associated with crop yield.

Over the past few decades, vegetation indices (VIs) have been widely applied for crop yield prediction (Jin *et al*., 2017; Kamir *et al*., 2020). Many studies have relied on vegetation indices from the visible and near-infrared spectrum, such as NDVI and EVI (Peng *et al*., 2010; Cunha and Silva, 2020). While these indices effectively indicate vegetation vigor, they may

not capture the full impact of environmental stresses on crop growth (Zhang *et al.*, 2021). Therefore, the inclusion of additional vegetation indices becomes important for improving yield estimation. Vegetation indices like the Normalized Difference Water Index (NDWI), which reflects the water status of crops (Gao, 1996), and the Red Edge Position (REP), which responds to changes in the chlorophyll content, offer detailed information on crop health and help improve the accuracy of yield predictions. Crop growth models provide a method to address few of the limitations related to the remote sensing-based yield estimation. These models simulate the underlying biophysical processes governing crop development and yield formation (de Wit *et al*., 2018). Over the several years, several process-based models has been developed for predicting agricultural productivity, including widely used systems such as DSSAT, WOFOST (Van Diepen *et al*., 1989), APSIM, and the AquaCrop (Steduto *et al*., 2009). These models are capable of representing the complete crop growth cycle by incorporating interactions among soil, weather conditions, and management practices.

AquaCrop, created by the Food and Agriculture Organization (FAO), is intended to model crop development and yield under different water availability scenarios, covering both irrigated and rainfed conditions (Timothy *et al*., 2017; Krishna *et al*., 2022). This type of model is particularly useful for evaluating crop performance under different climate change scenarios and supports decision-making related to water management. It was primarily developed to address agricultural challenges in water-limited environments by focusing on optimizing water use and improving crop productivity.

AquaCrop simulates crop growth based on instead of the Leaf Area Index (LAI), which is commonly employed in the majority of other crop models, green canopy cover (CC). The percentage of the soil surface that is shaded by the crop canopy is often referred to as the "green canopy cover," which ranges from zero at sowing to a maximum value (CCx) at the mid-season stage, where full canopy development may result in complete ground coverage (Salman *et al*., 2021). In addition, the model simulates above-ground biomass (B), which accounts for the total photosynthetic production accumulated by the crop over the growing period. Crop yield (Y) is subsequently estimated by applying the harvest index (HI), defined as the fraction of total biomass that contributes to the economic yield. The harvest index, however, is not constant and may deviate from its reference value (HI_0) under varying environmental conditions. Factors such as water stress, temperature extremes, and their timing during critical growth stages significantly influence HI. In particular, intense water stress or adverse temperature conditions

during critical growth stages such as pollination can significantly reduce yield by affecting how biomass is distributed within the plant (Salman et al., 2021). To achieve reliable calibration of the AquaCrop model, essential plant variables including green canopy cover (CC) and above-ground biomass (AGB) are needed, and these are typically collected through field measurements. However, acquiring such detailed ground measurements across large areas is often challenging. Conducting controlled experiments at research farms is possible, but these activities demand considerable time, labor, and financial resources, as continuous data collection throughout the crop growth cycle is necessary.

Wheat ranks among the most grown cereal crops across the whole world and serves as a key component of global food security (Cuong *et al.*, 2020). Global wheat production has reached approximately 778.6 million tonnes, reflecting its significance as a staple crop. In India, during 2020–2021, wheat was grown over a covering the area of about 31.13 million hectares, with a total production of 109.58 million tonnes and an average productivity of 3521 kg/ha. A substantial portion of this production is utilized for domestic consumption, underscoring its importance in national food security (Panday *et al*., 2024). As one of the earliest domesticated crops, wheat has long served as a primary source of calories for human populations across diverse regions. It is self pollinate and long-day crop belonging to the Poaceae family and is well adapted to dryland and semi-arid environments (Belderok *et al*., 2000). Due to its wide adaptability and nutritional value, wheat remains a key component of diets, particularly in resource-limited regions, where it contributes significantly to daily carbohydrate intake.

In the Indian context, wheat ranks as the second most important cereal crop after rice and is mainly grown during the Rabi season under cool and dry climatic conditions in states including Gujarat, Haryana, Punjab and Uttar Pradesh. Its versatility in consumption - from traditional foods to processed products such as bread, biscuits, cakes, and noodles - has further increased its demand. Additionally, wheat by-products such as straw and bran are widely used as livestock feed. Despite its importance, achieving optimum productivity continues to be a challenge, with factors such as inadequate nitrogen management and poor weed control significantly affecting crop establishment, growth, and final yield (Panday *et al*., 2024).

Under the Copernicus programme, the European Space Agency’s Sentinel-2 mission has strengthened routine agricultural monitoring by providing detailed imagery of vegetation, soil conditions, and water bodies across inland and coastal regions. The satellite is equipped

with a Multispectral Instrument (MSI) that acquires data across 13 spectral bands at spatial resolutions of 10 m, 20 m, and 60 m, with a revisit interval of approximately five days at the equator. The Sentinel 2 program consists pair of satellites, Sentinel 2A and Sentinel 2B that function together in coordinated orbits, shortening the revisit interval from about 10 days to nearly 5 days and thereby enhancing the frequency of data acquisition. The MSI sensor collects key spectral data at varying resolutions, with the four principal bands - blue, green, red, and near-infrared available with a spatial resolution of 10 meters. Bands in the red-edge region (B5, B6, B7, B8A) along with shortwave infrared bands (B11, B12) are provided at a 20 m spatial resolution, whereas atmospheric bands such as coastal aerosol (B1), water vapor (B9), and cirrus (B10) are available at comparatively coarser resolution. This multi-resolution and multi-spectral capability enables detailed assessment of crop conditions and biophysical parameters. Despite advancements in remote sensing, field-scale yield estimation remains challenging, particularly in regions dominated by smallholder farming systems. Satellite datasets with moderate spatial resolution, including MODIS (250 m) and Landsat (30 to 60 m), are often insufficient for precise monitoring of small and heterogeneous agricultural plots, which are widely prevalent in regions such as India (Elders *et al*., 2022). In these context, high-resolution satellite data become essential for precise crop monitoring and yield assessment. The Sentinel-2 mission addresses this limitation by providing open access imagery at 10 m spatial resolution with frequent revisit cycles. Such characteristics make it highly suitable for field-level agricultural applications, including crop health assessment and yield prediction (Kumar *et al*., 2022; Lonare *et al*., 2022; Sisheber *et al*., 2024).

A change in climate has emerged as a major concern for global food production, primarily due to its impact on water availability and agricultural systems across different regions (Smith, 2013; Hanjra and Qureshi, 2010). Changes in the spatial and temporal distribution of the rainfall, along with fluctuations in key resources such as water, land, biodiversity, and capital, are expected to influence food security and agricultural productivity (Lin, 2011). In India, although total food production has increased significantly over the past few decades and has outpaced population growth, this progress has come at the cost of increasing pressure on natural resources. Continuous intensification of agriculture has led to land degradation and excessive exploitation of groundwater resources. Furthermore, the heavy reliance of Indian agriculture on monsoon rainfall increases its sensitivity to fluctuations in weather patterns and evolving climate conditions over time. Wheat production, especially in northern India, is highly sensitive to temperature fluctuations. Studies have shown that crop

growth is adversely affected when temperatures approach or exceed critical thresholds, such as 34 °C during key growth stages (Lobell *et al*., 2012). According to projections by the Inter-governmental Panel on Climate Change (IPCC), even a small rise in the winter temperatures may reduce wheat yields, with an expected decrease of approximately 0.45 t/ha for every 0.5 °C increase in temperature (Easterling *et al.*, 2007).

Climate simulation models at the global scale are widely applied to estimate future climate patterns and assess their possible impacts on agricultural systems (Yang *et al.*, 2018). When integrated with crop simulation models, they enable a comprehensive assessment of how changing climate scenarios may affect crop growth and yield, particularly for major staple crops across different regions (Stevens and Madani, 2016). Such integrated approaches allow for the analysis of interactions among weather variables, land characteristics, and management practices, thereby supporting both global and regional-scale agricultural assessments.

Despite their usefulness, GCM-based simulations are inherently complex due to the involvement of multiple interacting processes, including atmospheric dynamics, physical mechanisms, and biogeochemical cycles driven by changes in greenhouse gas concentrations and their radiative forcing (Taylor *et al*., 2012). In addition, the coarse spatial resolution of GCM outputs, typically around 50 km × 50 km, limits their direct applicability for local-scale agricultural studies (Peng, 2022).

10. Practical Utility of the Research Project

The present investigation, titled *"*Water Conservation Strategies under Climate Change Scenarios Using Integrated Remote Sensing and AquaCrop Modelling*,"* is designed to develop a scientifically robust framework for improving the reliability of agricultural production assessment under changing climatic conditions. By integrating crop growth modelling with satellite-based observations and climate scenario analysis, the study will establish a comprehensive approach for estimating wheat yield across both field and regional scales. The use of vegetation indices derived from Sentinel-2 imagery will enable continuous, non-invasive monitoring of crop dynamics, thereby minimizing reliance on labor-intensive field measurements while ensuring spatial and temporal consistency in data acquisition.

The incorporation of the remotely sensed canopy information into AquaCrop model will enhance the accuracy of crop growth the productions simulations under the varying irrigation regimes and water management strategies. In addition, the study will explicitly

quantify water productivity, providing critical insights into the efficiency of water use in relation to crop yield. This will facilitate the identification of optimal water conservation strategies aimed at maximizing agricultural output Under conditions of restricted water supply, which is particularly relevant for semi-arid and water-stressed regions.

Furthermore, the integration of a calibrated AquaCrop model with the climate projections derived from Global Climate Models (GCMs) will enable the simulation of the crop performance under future climate scenarios. This approach enables a structured assessment of how variations in temperature and rainfall may affect wheat production. The outcomes will support farmers and agricultural planners in optimizing irrigation scheduling, crop management practices, and resource allocation. At the same time, the findings will provide the scientific basis for policymakers to formulate region-specific strategies for sustainable water use and climate-resilient agricultural development.

In addition, the research will contribute to a deeper understanding how climate variability influences crop production and water productivity, thereby aiding in the identification of suitable adaptation measures to mitigate adverse impacts. The developed methodology will support early yield forecasting, large-scale crop monitoring, and improved planning for food security under future climatic uncertainties.

Overall, this research will serve as an advanced decision-support framework for precision agriculture by enabling data-driven management practices, regional yield assessment, and the efficient utilization of water resources. The integration of remote sensing, crop modelling, and climate projections will not only improve yield prediction accuracy but also strengthen strategies for water conservation, enhance water productivity, and promote long-term sustainability in agricultural systems under evolving climate scenarios.

11. Objectives

1. To estimate vegetation indices based on remote sensing imagery and evaluate their relationship with ground-based crop biophysical parameters.
2. To calibrate and validate the AquaCrop model for simulating crop yield and water productivity of wheat.
3. To integrate satellite-derived canopy parameters with the AquaCrop model to improve the accuracy of crop yield.

4. To evaluate the influence of different climate change scenarios on wheat production and water productivity.

12. Review of Literature

Wellens *et al.* (2017) evaluated the effectiveness of the AquaCrop plug-in design for field-scale winter wheat yield prediction in Belgium by incorporating satellite-derived fractional vegetation cover (fCover). The study combined multiple datasets, including field measurements, digital hemispherical photography, DMC satellite imagery (22 m resolution) for generating fCover time series during April–September 2015, meteorological observations from 125 stations, and soil information obtained from the Belgian Soil Geographical Database. A semi-automated framework developed in R was employed to assimilate fCover into the model, while key parameters such as Water Productivity (WP), Harvest Index (HI), Canopy Growth Coefficient (CGC), and Canopy Decline Coefficient (CDC) were calibrated through iterative simulations, excluding soil fertility stress. The results showed a strong agreement between simulated and observed canopy cover (R^2 = 0.90, RMSE = 1.5%) across 11 wheat fields, and yield estimates were also closely aligned with measured values (RMSE = 0.8 t ha^{-1}), demonstrating the reliability of combining satellite-derived information with the aquacrop model for precise field-level yield estimation.

Dubey and Sharma (2018) investigated the influence of climatic change on the yield of important crops in Rajasthan, India's Banas River Basin, representing a semi-arid agro-climatic region. The analysis focused on wheat, maize, and barley using historical data for the duration 1981–2010 along with projection of future climate for 2021–2050. Meteorological inputs, including temperature and rainfall, were acquired from the Indian meteorological Department, while future climate data were sourced from the CORDEX-South Asia initiative, based on multiple GCMs under RCP 4.5 and RCP 8.5 scenarios. The FAO AquaCrop model was employed to simulate crop yields, with climate inputs adjusted using the delta bias-correction approach. Model validation and calibration were performed using observed yield data, and performance was evaluated through statistical indicators such as RMSE and model efficiency. The results demonstrated satisfactory model performance and indicated a general growth in the crop yields under anticipated climate scenarios, with wheat showing the highest increase, followed by barley and maize.

Akumaga *et al.* (2018) evaluated the Niger River Basin's cereal crop yield in relation to climate change and possible response measures of West Africa, with a focus on maize,

sorghum, and millet grown under rainfed conditions across different agro-ecological zones. The study incorporated historical yield data along with daily climate records obtained from meteorological stations and the AgMERRA dataset, the nine bias-corrected GCMs under RCP 4.5 and RCP 8.5 scenarios were used to create future climate forecasts for the years 2021–2050. The initial poor soil fertility levels were taken into consideration when calibrating and validating the AquaCrop model. The results revealed moderate yield increases of approximately 2–6% for maize and sorghum in the Southern Guinea zone, whereas yield reductions ranging from 2% to 20% were observed in the Northern Guinea zone, with relatively stable yields for millet in the Sahel region. The study further demonstrated that adaptation strategies, including modification of sowing dates, adoption of improved crop varieties, and enhancement of soil fertility, led to substantial yield improvements, ranging from 20% to 180%, highlighting how important management initiatives are in lessening the negative effects of climate change.

Rashid *et al*. (2019) examined the effects of the impact of climate change winter wheat yield, water use, and water use efficiency (WUE) in the North China Plain using the AquaCrop model. The study employed baseline climatic data for the period 1984–2015, along with future projections derived from ten GCMs under RCP 2.6,4.5,6.0, and 8.5 scenarios for the 2040, 2060, and 2080, with daily weather data generated through the MarkSim weather generator. Model calibration and validation were conducted using field observations from the Luancheng experimental station. Various management scenarios, including full and deficit irrigation as well as mulching practices, were simulated to evaluate potential adaptation strategies. The findings indicated an overall increase in wheat yield and WUE under future climate conditions, primarily driven by elevated CO_2 concentrations and rising temperatures, although a reduction in crop duration was observed. Seasonal evapotranspiration showed a declining trend, including the implementation of methods like Deficit Irrigation and mulching further enhanced water use efficiency, emphasizing their importance in sustaining wheat production under changing climatic conditions.

Das *et al.* (2020) evaluated how crop productivity is affected by climate change in the Eastern Himalayan region, with particular emphasis on Sikkim, India. The study examined the projected yield responses of main crops, such as maize, wheat, and rice, using historical datasets (1998–2015) comprising climate variables, yield records, soil characteristics, and management practices from selected districts. Future climate scenarios were derived from

multiple global climate models under RCP 4.5 and the RCP 8.5 pathways, with bias correcting performed using the distribution of mapping techniques to enhance data reliability. In order to forecast crop yields in the future, the FAO AquaCrop model was calibrated and validated, and an uncertainty analysis was conducted to account for variability across different climate model outputs. The results indicated a general increase in crop productivity under projected climate scenarios, largely attributed to rising temperatures within favorable limits and elevated atmospheric CO_2 concentrations, although considerable uncertainty among model projections was observed.

Yue *et al.* (2020) developed an integrated approach for pre-harvest estimation and spatiotemporal mapping of grain output and winter wheat biomass in Beijing, China using the AquaCrop model and inexpensive UAV-based remote sensing. The study was conducted during the 2014–2015 growing season using 48 experimental plots subjected to varying irrigation and fertilizer treatments. Field measurements of (FVC), yield and biomass were collected, while high-resolution UAV RGB imagery (0.73 m) was processed to extract vegetation indices and texture features. A random forest regression model was applied to estimate biomass, whereas FVC was derived using index-based spectral information. Calibration of the AquaCrop model was performed at plot and pixel scales using an optimization-driven data assimilation approach, incorporating biomass and FVC as essential inputs. The results indicated that biomass-based and combined modelling approaches outperformed the use of FVC alone, with pre-harvest predictions showing satisfactory agreement for biomass (R^2 =0.61, nRMSE =18.5%) and grain yield (R^2 = 0.63, nRMSE =21.9%). Additionally, pixel-level mapping effectively captured spatial variability and crop stress conditions, demonstrating its potential for supporting informed decision-making prior to harvest.

Abi Saab *et al*. (2021) carried out a study to improve crop growth tracking and yield forecasting by combining crop simulation modeling with remote sensing data. in the Bekaa Valley of Lebanon under semi-arid Mediterranean conditions. The research was based on multi-season field experiments on winter wheat, where detailed ground observations, including crop growth parameters and meteorological data, were systematically collected. “In addition, Sentinel-2 multispectral imagery was utilized to derive essential vegetation parameters, including NDVI, canopy leaf area index, and fractional vegetation cover. The Field measurements were used to calibrate and validate the AquaCrop model. to ensure accurate

representation of crop growth dynamics. To further improve model performance, a data assimilation approach was implemented by incorporating satellite-derived FVC into the simulation framework, thereby refining canopy development representation within the model. The findings showed that this combined approach substantially improved the precision and reliability of crop growth modeling and yield prediction. Overall, the research demonstrated the efficacy of combining satellite-based observations with crop modelling techniques for improving agricultural monitoring and decision-making.

Parida *et al*. (2021) explored application of RS and crop simulation modelling for type of crop identification, yield estimation in the Hazaribagh district of Jharkhand, India. The study employed multispectral Sentinel-2B imagery in combination with ground-based agricultural data to map major Rabi crops and assess their productivity. A Support Vector Machine (SVM) algorithm was implemented for crop classification, while yield estimation was carried out using regression approaches alongside the AquaCrop model. The outcomes showed a high degree of categorization accuracy, and the estimated yields showed close agreement with observed values. The study demonstrated that the incorporation of satellite-derived information with crop modelling methods can provide reliable outcomes for both crop identification and yield prediction, thereby supporting their effective use in agricultural planning and management.

Rank *et al*. (2022) evaluated the simulation of Sweet corn (Zea mays L.) water footprints under various irrigation management techniques at Junagadh Agricultural University, Gujarat, during the Rabi seasons of 2020-21 and 2021-22. The study combined field experimental observations with the FAO AquaCrop model, incorporating inputs such as climatic variables, soil characteristics, crop parameters, and various irrigation - fertigation treatments. A total of 16 treatment combinations were assessed, representing different levels of water stress, fertigation regimes, drip irrigation methods (surface and subsurface), and mulching practices. Observations of canopy cover, biomass, yield, and water footprint were used to calibrate and validate the AquaCrop model. components were subsequently estimated from model simulations. The results demonstrated satisfactory model performance, with a strong agreement between the simulated and observed values, as indicated by statistical measures like Willmott's index, correlation coefficient, and Nash-Sutcliffe efficiency. Overall, the model effectively captured crop growth dynamics and water footprint variations under different irrigation conditions, although slight deviations were noted, particularly in the estimation of biomass.

Li *et al*. (2024) investigated the incorporation of unmanned aerial vehicle (UAV)-based RS with the AquaCrop model to enhance simulation of crop yield, growth in a tea plantation in Jiangsu Province, China. The study incorporated field observations along with UAV-derived multispectral imagery, from which vegetation indices and canopy cover information were extracted. Statistical and regression-based approaches were developed to estimate canopy cover, and a Particle Swarm Optimization (PSO) algorithm was employed to assimilate the remotely sensed canopy data into the AquaCrop model. The results revealed strong relationships between vegetation indices and canopy cover, with the Optimized Soil-Adjusted Vegetation Index (OSAVI) providing the highest estimation accuracy. The integrated AquaCrop - PSO framework significantly enhanced model functionality and yield prediction accuracy compared to the conventional model setup, demonstrating the potential of combining UAV-based RS with crop simulation models for more precise agricultural assessment.

Ghazouani *et al*. (2025) assessed the capability of the AquaCrop model to estimate soil water content and durum wheat yield under semi-arid Mediterranean conditions in northwest Tunisia through the integration of remote sensing and reanalysis datasets. The study was based on field observations collected during the 2024-2025 growing season, including meteorological parameters, green canopy cover, soil moisture, and grain yield, supplemented with Sentinel-2 NDVI data and ERA5-Land reanalysis products. Four different combinations of ground-based and satellite-derived inputs were evaluated to determine their influence on model performance, which was quantified using statistical indicators like RMSE, (NSE), and (R^2). The findings indicated that Sentinel-2 data effectively represented canopy dynamics, while ERA5-Land provided reasonably accurate estimates of temperature and evapotranspiration, although some inconsistencies were observed in precipitation data. The model produced biological yield estimates ranging from 9.7 to 11.0 tha^{-1} and grain yield values between 3.0 and 3.5 t ha^{-1}, closely matched the values that were observed in 10.3 and 3.3 tonnes per hectare, respectively. Overall, the results demonstrated the integration of remote sensing and reanalysis data with the AquaCrop model can serve as a reliable approach for crop monitoring and water management, particularly in regions with limited availability of field data.

Giri *et al.* (2026) assessed how well the AquaCrop model simulated wheat yield and growth under varying temperature and rainfall conditions in the humid subtropical region of Delhi-NCR, India. The research was done over three consecutive cropping seasons (2021–2024) and included different irrigation practices, namely drip and conventional flood irrigation. Field

observations comprising crop growth attributes, soil moisture status, and weather parameters were collected, along with UAV-based multispectral data used to estimate canopy cover (CC). The calibration of model was done using the data from the first season and subsequently validated with independent datasets from the following seasons. Furthermore, UAV-derived CC was integrated into the model to improve its predictive capability. The results indicated a strong agreement between simulated and observed biomass and grain yield, with coefficient of determination (R^2) values were from 0.89 to 0.95 and (NSE) values in between 0.85 to 0.94. The coupling of UAV-based CC further enhanced model performance, achieving higher accuracy (R^2 up to 0.98) and lower RMSE, thereby demonstrating the advantage of combining remote sensing inputs with AquaCrop under variable climatic conditions.

13. Materials and Methods

The methodology integrates remote sensing data, crop growth modelling and climate scenario analysis.

13.1 Description of the Study Area

13.1.1 Location

Farm of Junagadh Agricultural University will be selected for this research work which is located in Junagadh, Gujarat.

13.1.2 Climate

A characteristic of the study area is a subtropical semi-arid environment, featuring cool and drier conditions in winter, extremely hot and dry summers, and comparatively warm weather with moderate humidity during the monsoon period. The region receives about 1100 mm of rain on average each year. January is recorded as the coldest month, with average minimum temperatures ranging between 7°C and 10°C; May, on the other hand, has the highest average temperature, usually between 35 and 45 degrees Celsius.

13.2 Experiment details

a. Crop: Wheat (*Triticum aestivum* L)
b. Crop growing season: Rabi season
c. Irrigation: Border Irrigation

13.3. Data Collection

13.3.1 Climate data

a. Rainfall
b. Temperature
c. Relative humidity
d. Solar radiation
e. Wind speed

13.3.2 Soil data

To simulate soil water dynamics, the AquaCrop model requires detailed information on key physical properties of soil. The soil parameters will be estimated by collecting representative soil samples from field and analyzing them under controlled laboratory conditions.

13.3.3 Satellite data

Sentinel-2B imagery covering the Junagadh area will be obtained from the Copernicus Data Space Ecosystem.

13.4 Ground-Based Measurement

13.4.1 Measurement of Leaf Area Index Using Plant Canopy Analyzer

Leaf Area Index (LAI) of the wheat crop will be recorded using the LAI-2200 Plant Canopy Analyzer manufactured by LI-COR Biosciences, USA.

13.4.2 Measurement of NDVI Using Handheld NDVI Meter

The FieldScout CM 1000 NDVI Meter will be employed as a handheld, portable device to evaluate plant health non-destructively using NDVI measurements.

13.4.3 Soil Moisture

Soil moisture content will be determined using either the Time Domain Reflectometry (TDR) technique or the gravimetric approach to ensure accurate and dependable measurement of soil water status.

13.4.4 Field Measurement of Biomass

For estimating the biomass of winter wheat, plant samples will be collected and analyzed. The samples will be cut, placed in paper bags, and dried in an oven to remove their moisture content before measurement.

13.4.5 Determination of Reference Evapotranspiration

The FAO Penman - Monteith equation, as proposed by Allen et al. (1998), will be applied to determine ET_0.

$$\mathrm{ETo} = \frac{0.408\,.\,\Delta\,.(\mathrm{Rn}-\mathrm{G}) + \gamma.\frac{900}{T+273}.(es-ea)}{\Delta + \gamma\,.(1+0.34.u2)} \quad (1)$$

Where,

Rn = Net radiation available at the crop canopy surface (MJ/m^2 day),

G = Soil heat energy flux per unit area (MJ/m^2 day),

T = Daily mean temperature of air recorded at 2 m above ground level (°C),

u_2 = Wind speed observed at 2 m elevation (m/s),

es = Vapor pressure corresponding to saturated air (kPa),

ea = Existing water vapor pressure in the air (kPa),

es – ea = Difference between saturation and actual vapor pressure (kPa),

Δ = "Rate of change of saturation vapor pressure with temperature (kPa/°C),

γ = Psychometric constant (kPa/°C)

13.4.6 Determination of the Crop Evapotranspiration

The evapotranspiration associated with the crop, denoted as ETc, will be estimated using the crop coefficient method.

$$\sum_{i=1}^{3} \mathrm{ETci} = \sum_{i=1}^{3} \mathrm{Kci}\ \mathrm{ET0i} \quad (2)$$

Where

ET_{ci} = Crop evapotranspiration of i^{th} day,

K_{ci} = Crop coefficient of i^{th} day,

ET_{0i} = Reference evapotranspiration of i^{th} day

13.4.7 Converting the Leaf Area Index (LAI) to Canopy Cover (CC)

Leaf Area Index (LAI) will be converted into canopy cover (CC), as canopy cover is needed to represent crop development in the model, while field measurements are generally available in terms of LAI during parameterization. The conversion will be carried out using the relationship proposed by Hsiao *et al*. (2009):

$$CC = 1.005[1-e^{-(0.6*\,LAI}]^{\,1.2}$$

13.4.8 Water Productivity

Water productivity refers to the amount of yield produced per unit of water used. It can be represented through several water productivity (WP) indices, which are expressed as follows:

$$WIP_{irr} = \frac{Yield}{IR+RF} \quad (3)$$

$$WIP_{IR} = \frac{Yield}{IR} \quad (4)$$

$$WIP_{IR + ER} = \frac{Yield}{IR+RF\ eff} \quad (5)$$

$$WIP_{ETc} = \frac{Yield}{ETc} \quad (6)$$

Here, WPI stands for the fraction of water productivity, IR is the amount of irrigation water needed (m^3), RF represents the total rainfall (m^3), RFeff is the effective portion of rainfall (m^3), and ETc refers to the actual water consumed by the crop through evapotranspiration (m^3).

13.5 Satellite Data and Vegetation Indices

The condition of vegetation cover on the land surface will be assessed using vegetation indices, which will be derived to track and evaluate temporal changes.

13.5.1 Soil Adjusted Vegetation Index (SAVI)

The Soil Adjusted Vegetation Index (SAVI) will be computed using spectral reflectance data to reduce the influence of soil background and to assess vegetation density and vigour (Huete, 1988).

$$SAVI = \frac{(NIR - RED)(1 + L*)}{(NIR - RED + L*)} \quad (7)$$

13.5.2 Enhanced Vegetation Index (EVI)

The Enhanced Vegetation Index (EVI) will be derived to assess vegetation greenness, offering better sensitivity in areas with high biomass while minimizing the effects of atmospheric interference and canopy background (Huete *et al*., 2002; Hatfield and Prueger, 2010).

$$\mathrm{EVI} = \mathrm{G} * \frac{(\mathrm{NIR} - \mathrm{R})}{(\mathrm{NIR} + \mathrm{C1} * \mathrm{R} - \mathrm{C2} * \mathrm{B} + \mathrm{L}))} \quad 8$$

13.5.3 Leaf Area Index (LAI)

Leaf Area Index (LAI) will be estimated to evaluate canopy density and photosynthetic activity, thereby aiding in the assessment of crop growth and predicting crop yield. The calculation of LAI will be carried out using the relationship proposed by Boegh *et al*. (2002):

$$\mathrm{LAI} = (3.618 * \mathrm{EVI} - 0.118) \quad 9$$

$$\mathrm{LAI} = \frac{-\ln(\frac{\mathrm{SAVI}-0.65}{0.39})}{0.33} \quad 10$$

13.5.4 Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) will be derived from reflectance values in the red and near-infrared bands to evaluate vegetation cover and greenness. This index was originally developed by the Rouse *et al*. (1974).

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{RED}}{\mathrm{NIR} + \mathrm{RED}} \quad 11$$

13.6 AquaCrop Model

13.6.1 AquaCrop input parameters

The AquaCrop model is designed to function with a concise set of well-defined and easy-to-handle parameters and input variables, most of which are readily available or can be obtained through straightforward methods. The primary inputs required for the model include climatic data, crop characteristics, soil properties, and information on field and irrigation management practices that collectively describe the growing conditions of the crop.

Climatic data can be supplied at daily, 10-day, or monthly time scales. In situations where daily observations are unavailable, the model uses internal procedures to derive daily values from 10-day or monthly averages, which are then used as the simulation time step (Raes *et al*., 2023). However, the use of aggregated rainfall data at longer intervals is generally discouraged, as it may not adequately represent the variability in water availability and its

influence on crop response. Additionally, AquaCrop provides an inbuilt option to compute reference evapotranspiration (ET_0) from climatic inputs using the FAO Penman–Monteith method, as described by Allen *et al*. (1998).

13.6.2 Model calibration and validation

In this study, the AquaCrop (AC) model will be applied to analyze growth of crop behavior such as biomass accumulation and the yield under varying water and nitrogen conditions. Canopy development in the model is represented through canopy cover (CC), which is conceptually equivalent to fractional vegetation cover (FVC). In the present work, FVC will be estimated from Sentinel-2 satellite data.

Model calibration will be carried out using field observations obtained under irrigated conditions for a selected growing season. The calibration process will be conducted iteratively by integrating recorded crop growth at different stages, measured crop growth parameters, estimated crop coefficients, and other relevant inputs, following the guidelines provided in the AquaCrop user manual. Model validation will then be performed using independent datasets collected from different seasons. The simulated results will be systematically compared with observed field data across all treatments to assess the accuracy and reliability of the model.

13.7 Integrating AquaCrop and Sentinel Data

The present study will adopt an integrated approach that combines the AquaCrop model with the remote sensing data to improve the irrigation management analysis in wheat. This integration will be achieved by linking crop parameters derived from Sentinel-2 imagery with AquaCrop.

In particular, fractional vegetation cover (FVC) obtained from Sentinel-2 data will be periodically incorporated into the model by replacing the simulated canopy cover (CC). This stepwise updating approach will be based on the assumption that continuous assimilation of remotely sensed observations can reduce uncertainties associated with model simplifications and environmental variability, thereby enhancing the accuracy of crop growth simulation.

13.8 Climate Change Scenarios

Future climatic conditions across different time periods and greenhouse gas emission scenarios will be projected using General Circulation Model (GCM)-based climate modelling techniques. The study will utilize CMIP6 models developed within the framework of Shared Socioeconomic Pathways (SSPs) to examine possible climate variations over the 21st century. The assessment will primarily emphasize overall climate variability and its impact on crop productivity, without specifically addressing drought-related projections.

Mishra *et al*. (2020) created the daily bias-corrected datasets for rainfall, as well as maximum and minimum temperatures, at a spatial resolution of 0.25° covering the South Asian region, including India, Nepal, Bhutan, Pakistan, Bangladesh and Sri Lanka, along with 18 major river basins in the Indian subcontinent. Bias correction was performed using the Empirical Quantile Mapping (EQM) approach for the historical period (1951–2014) as well as future projections (2015–2100) under four SSP scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5), utilizing outputs from 13 CMIP6 GCMs.

Following a similar framework, the present study will use the bias-corrected daily datasets of rainfall, max temperature (Tmax), and min temperature (Tmin) provided by Mishra *et al*. (2020) for 13 GCMs corresponding to the selected region. Datasets with a spatial resolution of 0.25° × 0.25° will be sourced from the Zenodo repository for the study region, covering the historical period from 1981 to 2014 and the future projections from 2026 to 2099 under SSP2-4.5 and SSP5-8.5 scenarios. These climate inputs will be employed to assess climate change scenarios and will be integrated with AquaCrop modelling and remote sensing approaches to analyze crop growth, yield, and water productivity under projected future conditions.

14 Statistical Analysis

Statistical techniques will be applied to determine the level of agreement between observed field measurements and values generated by the AquaCrop model or derived from the Sentinel-2 imagery. The performance of the model and the dependability of vegetation indices will be evaluated through commonly used statistical measures, such as the root mean square error (RMSE), the coefficient of variation of RMSE [CV(RMSE)], and the Nash–Sutcliffe efficiency (NSE). Among these indicators, RMSE will be used to represent the average difference between observed and simulated values, and it is expressed as:

$$RMSE = [N \sum_{i=1}^{N} (P_{i-}O_i)^2]^{0.5}$$

Here, N denotes the total no. of paired observations, where O_i represents the observed values and P_i corresponds to the respective simulated or predicted values. To normalize RMSE, the coefficient of variation [CV(RMSE)] will be calculated by expressing RMSE relative to the mean of the observed values ($\bar{O}$), as presented below

$$CV(RMSE) = \frac{RMSE}{\tilde{O}}$$

Modelling efficiency, expressed as NSE, quantifies how well a model's predictions match observed data and is calculated as:

$$N\ S\ E = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \tilde{O})^2}$$

This indicator expresses the proportion of residual variance relative to the variability observed in the measured data (Nash and Sutcliffe, 1970). According to Abi Saab *et al*. (2019), model performance based on Nash–Sutcliffe efficiency (NSE) can be categorized as follows: values between 0.90 and 1.00 indicate very good performance, 0.80 to 0.899 reflect good performance, 0.65 to 0.799 are considered acceptable, and values below 0.65 denote poor performance.

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